Assignment 6: Semantic Segmentation on the ACDC Dataset

1. Results Summary

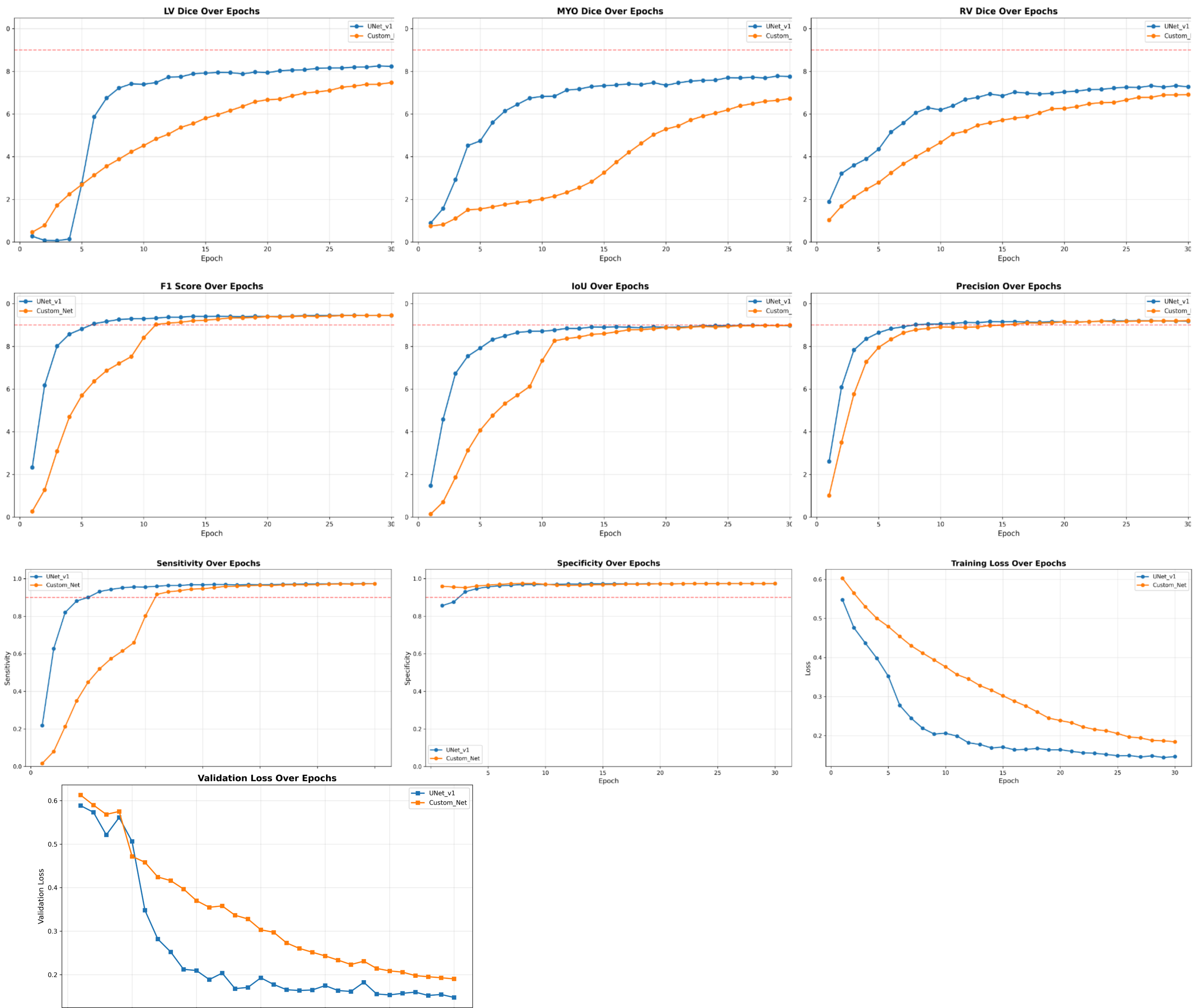
UNet_v1 (200 samples, no augmentation):

F1 = 0.981   IoU = 0.964   Precision = 0.981   Sensitivity = 0.981

Full dataset with augmentation (30 epochs):

Model	Specificity	F1	IoU	Sensitivity	Precision
UNet_V1	0.973	0.947	0.902	0.975	0.922
Custom Model	0.974	0.945	0.898	0.973	0.919

UNet_v1 slightly outperformed Custom_Net, especially on MYO and RV, thanks to richer multi-scale skip connections.



2. Data Augmentation and Transformation Choices

Data augmentation greatly improved **generalization** and prevented **overfitting** when scaling from 200 to 1076 samples.

Transformations were chosen to reflect real MRI variability while preserving anatomy:

Flips (p = 0.5) for orientation diversity, **±15° rotations** for patient positioning, **Gaussian blur (σ = 0.1–0.5)** and **random sharpness (p = 0.3)** for scanner and motion differences.

Color jitter and elastic deformation were avoided to maintain anatomical validity.

These augmentations exposed models to realistic variations in orientation, resolution, and contrast, yielding **F1 > 0.94** and consistent performance on unseen patients.

3. Metric Trade-offs

Both models achieved high sensitivity (~0.97) with slightly lower precision (~0.92).

This reflects a deliberate bias toward false positives rather than false negatives—appropriate for medical imaging, where missing cardiac tissue is riskier than minor over-segmentation.

Weighted Dice Loss emphasized cardiac structures, yielding specificity ≈ 0.97 while preserving aggressive tissue detection.

4. Custom Model Performance

Custom_Net (2.3M parameters) used fewer ConvBlocks and one global skip connection, trading fine-grained detail for efficiency.

- Lower per-class Dice for thin myocardium (0.67 vs 0.79 in UNet_v1)
- ~30% faster inference, smaller memory footprint

UNet_v1's multi-level skip connections retained spatial detail and produced more anatomically accurate segmentations, especially for thin myocardial walls.

5. Common Failure Modes

1. Poor delineation of thin myocardium, especially near the apex
2. Over-smooth boundaries from Dice loss compactness bias
3. Ambiguity at apical regions where structures converge
4. Low-contrast slices causing MYO–LV confusion despite augmentation

6. Comparison to Detection Results (Assignment 5)

Assignment 5 (YOLOv8-nano on MNISTDD-RGB) achieved IoU = 0.86 with bounding-box detection.

In contrast, segmentation here achieved IoU = 0.90–0.96 at the pixel level, critical for measuring cardiac wall thickness and ventricular volume.

Detection provides coarse localization, while segmentation yields quantitative clinical precision—though at higher computational cost (≈50–100 ms / image).